

Homework 1+M (Q1)

(Q1) 1-period Bitcoin mining:-

expend $\rightarrow \alpha > 0$; prob of winning (p) = $\frac{\alpha}{\alpha+A}$

$$\text{Gain/Loss} = rZ - C\alpha \quad \left(\begin{array}{l} \text{if win} \\ \text{if loss} \end{array} \right) = \begin{cases} r - C\alpha & \text{if win} \\ -C\alpha & \text{if loss} \end{cases}$$

$r = \frac{r}{A} M + A$

$$E(P_r) = p(r - C\alpha) + (1-p)(-C\alpha) = rp - C\alpha$$

$$= \frac{r\alpha}{\alpha+A} - C\alpha = f(\alpha)$$

$$(a) \alpha^* \Rightarrow \frac{\partial E(P_r)}{\partial \alpha} = 0 \Big|_{\alpha=\alpha^*} \Rightarrow \frac{r(\alpha+A-\alpha)}{(\alpha+A)^2} - C = 0 \Big|_{\alpha=\alpha^*}$$

$$\Rightarrow \frac{rA}{(\alpha^*+A)^2} = C \Rightarrow \boxed{\alpha^* = \sqrt{\frac{rA}{C}} - A} \quad \begin{cases} \text{if } C \leq \frac{r}{A}; \\ \text{if } C > \frac{r}{A}, \alpha^* = 0 \end{cases}$$

$$\frac{\partial^2 f}{\partial \alpha^2} \Big|_{\alpha=\alpha^*} = \frac{-2rA}{(\alpha^*+A)^3} < 0 \Rightarrow \alpha^* \text{ is maximiser of } f(E(P_r))$$

$$A = \left(\frac{r}{C} - 1 \right) \frac{A}{r} =$$

$$(b) \alpha^* = 0 \Rightarrow \boxed{C^* = \frac{r}{A}} \quad \left(\sqrt{\frac{rA}{C}} - A \leq 0 \Rightarrow \sqrt{\frac{rA}{C}} \leq A \right)$$

$$\Rightarrow \frac{rA}{C} \leq A^2 \Rightarrow A \geq \frac{r}{C}$$

$$A = \sqrt{r(A-\mu)} \quad M =$$

(c) $M+1$ miners with different costs of electricity;
interacting through A

$$A \sim M\bar{\alpha} : \text{assuming distribution of electricity costs is by } m(c)$$

$\rightarrow A \rightarrow c \rightarrow \alpha^*(c)$

$\rightarrow A = M \bar{\alpha}$ with $\bar{\alpha} = \int_{q-1}^{x_0+r} \alpha^*(c) m(c) dc$

mean α (hash) rate

$$\begin{aligned} \bar{\alpha} &\in [r, r] \\ r &= (x_0 - q) + (x_0 + r) q \quad \text{R} \quad (29) \\ \Rightarrow m(c) &= \frac{1}{r} \left[\frac{r}{2} \leq c \leq r \right] \end{aligned}$$

$$(i) \bar{\alpha} = \int \alpha^*(c) m(c) dc$$

$$\begin{aligned} \bar{\alpha} &= \int_{r/2}^{(x_0 - A + r)/2} \alpha^*(c) \frac{2}{r} dc \quad \text{R} = \frac{76}{206} \quad (29) \\ &= \int_{r/2}^{(x_0 - A + r)/2} \left(\sqrt{\frac{rA}{c}} - A \right) \frac{2}{r} dc \end{aligned}$$

$$\begin{aligned} &= \frac{2}{r} \sqrt{rA} \left[\frac{1}{2} \ln \left(\frac{rA}{c} \right) \right]_{r/2}^{(x_0 - A + r)/2} \quad \text{R} = \frac{A \gamma}{(A + r)} \\ &= \frac{2}{r} \sqrt{rA} \left[\frac{1}{2} \ln \left(\frac{rA}{c} \right) \right]_{r/2}^{(x_0 - A + r)/2} \quad \text{R} = \frac{A \gamma}{(A + r)} \\ &= 4 \sqrt{\frac{A}{r}} \left(\sqrt{r} - \frac{\sqrt{r}}{\sqrt{2}} \right) - A \end{aligned}$$

$$A \geq \frac{4}{3} \sqrt{rA} \left(1 - \frac{1}{\sqrt{2}} \right) - \frac{\sqrt{rA}}{3} \quad \boxed{\frac{\gamma}{A} = 3} \quad \text{R} = 0 \quad (d)$$

$$\left(\frac{\gamma}{A} \right) = \underline{(4 - 2\sqrt{2})\sqrt{rA}}$$

$$\begin{aligned} A &= M \bar{\alpha} \\ &= M \left((4 - 2\sqrt{2})\sqrt{rA} - A \right) \end{aligned}$$

②

$$\sqrt{A} = M(4 - 2\sqrt{2} - \sqrt{A})$$

$$\Rightarrow \sqrt{A} = \frac{M(4 - 2\sqrt{2})}{1+M}$$

$$\Rightarrow A = \frac{8M^2(\sqrt{2}-1)^2}{(1+M)^2}$$

$$\begin{aligned}\Rightarrow \bar{\alpha} &= \sqrt{A}(4 - 2\sqrt{2} - \sqrt{A}) \\ &= \frac{M(4 - 2\sqrt{2})}{1+M} \left(4 - 2\sqrt{2}\right) \left(1 - \frac{M}{1+M}\right) \\ &= \frac{M \cdot 8 \cdot (\sqrt{2}-1)^2}{(1+M)^2} \\ &= \frac{8M(\sqrt{2}-1)^2}{(1+M)^2}\end{aligned}$$

$$\begin{aligned}(\text{i.}) \quad \text{For } M \rightarrow \infty, A &\rightarrow 8(\sqrt{2}-1)^2 \\ &= 8 \cdot 0.41^2 \\ &\approx 8 \cdot 0.16 \\ &\sim 1.28 \subseteq (1, 2) \checkmark\end{aligned}$$

(iii)

c^* is s.t.

$$\alpha^*(c^*) = 0 \quad (\& \alpha^*(c) = 0 \& c \in [c^*, r])$$

$$\alpha^*(c^*) = \sqrt{\frac{rA}{c^*}} - A = 0 \Rightarrow c^* = \frac{r}{A}^{M+1}$$

$$\Rightarrow c^* = \frac{r}{8M^2(\sqrt{2}-1)^2} \stackrel{=} {\boxed{\frac{r(1+M)^2}{8M^2(\sqrt{2}-1)^2}}}$$

$$\frac{(1-\beta V) \cdot 8 \cdot M}{(M+1)}$$

$$\frac{(1-\beta V) M 8}{(M+1)}$$

$$\frac{(1-\beta V) \cdot 8 \cdot M}{(M+1)} \leftarrow A, \infty + M \text{ not } (ii)$$

$$12 \cdot 0 + 8 =$$

$$12 \cdot 0 + 8 = 8$$

$$\sim (2,1) \rightarrow 82.1 \sim *$$

(Q.2) Now, $p = \frac{\alpha x}{\alpha x + Ax}$ (Here, α (most probably) represents
cost of elec/hash • # hashes/\$

$\rightarrow H(\text{profit}) = rz - \alpha$

$E(H) = rE(z) - \alpha = rp - d = \frac{r\alpha x}{\alpha x + Ax} - \alpha$

Expected profit and other terms $\Rightarrow E(H) = \frac{r(1 - \frac{Ax}{\alpha x + Ax}) - \alpha}{\alpha x + Ax}$

and $\text{variance of profit} = \frac{rAx}{\alpha x + Ax} - \alpha$

At this point we have $E(H) = \frac{r(1 - \frac{Ax}{\alpha x + Ax}) - \alpha}{\alpha x + Ax}$

(a) $f(x) = \frac{rAx}{\alpha x + Ax} - \alpha$

$\frac{\partial f}{\partial x} = \frac{rA - \alpha x^2}{(\alpha x + Ax)^2} = 0$

critical points at $x = \frac{rA}{\alpha}$ & $x = 0$

$\Rightarrow \frac{rAx^2}{(\alpha x + Ax)^2} = 1$

$$\Rightarrow \alpha^* x + Ax = \sqrt{rAx}$$

$$\Rightarrow \alpha^* = \frac{\sqrt{rAx}}{x} - A$$

\leftarrow	\leftarrow
\leftarrow	\leftarrow

(if $d = \frac{u}{x} \geq \frac{A}{r}$;
if $d \leq \frac{A}{r}$, $\alpha^* = 0$)

(b) Let $\frac{x}{d} = d$

$$\Rightarrow \alpha^* = \sqrt{\frac{rA}{d}} - A \leq 0 \Rightarrow \sqrt{\frac{rA}{d}} \leq A \Rightarrow \frac{rA}{d} \leq A^2$$

$$\Rightarrow d \leq \frac{A}{r}$$

(C) At wealth (x) increases firstly $x^* \uparrow$ (more chance of x^* being positive now) & also due to $x \uparrow$ & $\alpha \uparrow$, (assuming A & X are constant), p (prob. reward) \uparrow

So, the one with more wealth has more/higher chance of getting more wealth due to which the wealth gap/inequality is likely to increase. This supports the idea of preferential attachment.

Hence, instead of getting decentralized (where wealth distribution) inequality decreases & distribution is more uniform among players, here wealth inequality is increasing & so leads us to be against the idea of decentralized finance.

$$\overline{xxAY} = xA + x^* \Rightarrow$$

$$xA - \overline{xxAY} = x^* \Rightarrow$$

$$\frac{A}{\gamma} \leq \frac{x}{x} = b \quad (1)$$

$$(0 \leq x, \frac{A}{\gamma} \geq b \quad (2))$$

$$b = \frac{x}{x} \text{ to } (d)$$

$$\frac{A}{\gamma} \geq \frac{AY}{b} \Leftrightarrow \frac{A}{b} \geq \frac{AY}{\gamma} \Leftrightarrow 0 \geq \left(\frac{A}{b} - \frac{AY}{\gamma} \right) = x^* \Leftrightarrow$$

$$\boxed{\frac{A}{\gamma} \geq \frac{AY}{b}} \Leftrightarrow$$

Q. 3) Financialization

$$S_t = \epsilon \frac{A + G_S X_t}{A + \sigma_t^{(0)}}$$

(a) If A is very large, $S_t \rightarrow 0 \Rightarrow$ financialization correlation tends to 0.

In general, $S_t \propto \frac{1}{A}$ (Inversely proportional to A).

So, as $A \uparrow$, $S_t \downarrow$.

\Rightarrow compared to ~~say~~ if supply: A is small, S_t is large
If A is large, S_t is small.

\Rightarrow compared to supply being less, if supply is more,
correlation is less.

So, if A is large, S_t = small

If A is small, S_t = large (significant).

So, compared to A being ~~large~~^{small}, if $\underbrace{A}_{\text{supply}}$ were large,

the financialization correlation (S_t) would decrease (be less).

Why? If supply is smaller, every unit of the supply matters
(i.e. marginal utility of the units is high); So, correlation would kick on. However, if the supply is large,

the impact of speculators does not affect the actual trading or market of the commodity, thus decreasing S_t .

supply small

Supply large ~~desirous~~ ($\epsilon \cdot \vartheta$)

→ small market

→ large market

→ impact of speculators high
(how they trade)

→ spec. impact low

→ St. high

→ hence, SE law.

(b) Note that $\theta + \pi \leq 1$ (\because univeraged)

To maximize S_T $\propto \theta\pi$, $\boxed{\theta = \pi = \frac{1}{2}}$

$$\theta = \pi = \frac{1}{2}$$

$\downarrow +2$, $\uparrow A \infty$, ω

(transferring) $\log N = -2$, where $N \in A$ is

$$\log Y \in (-\infty, \infty) \Rightarrow Y \in (e^{-\infty}, e^{\infty}) = (0, \infty)$$

(a) $\log Y \sim N(\mu, \sigma^2)$ under risk-neutral prob. \mathbb{P}

$$E^{\mathbb{Q}} \{(1-Y)^+\} = \int_0^\infty (1-y)^+ f_Y^{\mathbb{Q}}(y) dy = \int_0^1 (1-y) f_Y^{\mathbb{Q}}(y) dy + \int_0^\infty \dots$$

$$= \int_0^1 (1-y) f_Y^{\mathbb{Q}}(y) dy$$

$$= \int_0^1 y f_Y^{\mathbb{Q}}(y) dy - \int_0^1 y f_Y^{\mathbb{Q}}(y) dy$$

$$= P(Y \leq 1) - \left[(y \int_0^1 f_Y^{\mathbb{Q}}(y) dy) \Big|_0^1 - \int_0^1 (y f_Y^{\mathbb{Q}}(y) dy) dy \right]$$

$$= P(\log Y \leq 0) - \left[(y F_Y^{\mathbb{Q}}(y)) \Big|_0^1 - \int_0^1 F_Y^{\mathbb{Q}}(y) dy \right]$$

$$= P(N(\mu, \sigma^2) \leq 0) - [F_Y^{\mathbb{Q}}(0)] + \int_0^1 F_Y^{\mathbb{Q}}(y) dy$$

$$\log Y = t \Rightarrow \frac{dy}{dt} = dt \quad (y = e^t)$$

$$\Rightarrow I = \int_{-\infty}^0 (-e^t) f_T^{\mathbb{Q}}(t) dt = \int_{-\infty}^0 f_T^{\mathbb{Q}}(t) dt - \int_{-\infty}^0 e^t f_T^{\mathbb{Q}}(t) dt$$

$$\text{So, } E^{\mathbb{Q}}((1-Y)^+) \neq -E^{\mathbb{Q}}((1-1)^+) \quad (dY = \mu dt + \sigma dZ)$$

$$(Y_T = \ln(\frac{S_T}{X_T})) = \ln(\frac{S_0}{X_0}) + (\mu + \sigma Z) T$$

From wikipedia, for a lognormal RV Y ,

$$g(k) = \int_k^\infty y f_Y^{\mathbb{Q}}(y) dy = e^{u+\sigma^2/2} \Phi\left(\frac{u-\ln k + \sigma}{\sigma}\right)$$

$$\Rightarrow g(1) = e^{u+\sigma^2/2} \Phi\left(\frac{u+\sigma^2}{\sigma}\right)$$

$$\Rightarrow \int_0^1 y f_Y^{\mathbb{Q}}(y) dy = E(Y) - g(1) = e^{u+\sigma^2/2} - e^{u+\sigma^2/2} \Phi\left(\frac{u+\sigma^2}{\sigma}\right)$$

$$\Rightarrow \text{Final answer} = E^{\mathbb{Q}}((1-Y)^+) = \boxed{\Phi\left(-\frac{u}{\sigma}\right) - e^{u+\sigma^2/2} \Phi\left(-\frac{u}{\sigma} - \sigma\right)}$$

Now? $y \sim x = \ln N(\mu, \sigma^2)$ ~~log normal~~ & $\ln x = y \sim N(\mu, \sigma^2)$

$$\int_{-\infty}^{\infty} x f_x(x) dx = E(x 1_{x>k}) = E(e^y 1_{e^y>k}) = E(e^y 1_{y>\ln k})$$

$$= \int_{\ln k}^{\infty} e^y f_y(y) dy = \int_{\ln k}^{\infty} e^y \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) dy$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int \exp\left(-\frac{(y-\mu+2\sigma^2)^2}{2\sigma^2} + y\right) dy$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int \exp\left(-\frac{y^2 + 2\mu y - \mu^2 + 2\sigma^2 y}{2\sigma^2}\right) dy$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int \exp\left(-\frac{[y - (\mu + \sigma^2)]^2 - (\mu + \sigma^2)^2 + \mu^2}{2\sigma^2}\right) dy$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int \exp\left(-\frac{(y - (\mu + \sigma^2))^2 + \frac{\mu^2 + 2\mu\sigma^2 + \sigma^4 - \mu^2}{2\sigma^2}}{2\sigma^2}\right) dy$$

$$= \exp\left(\mu + \frac{\sigma^2}{2}\right) \frac{1}{\sigma\sqrt{2\pi}} \int_{\ln k}^{\infty} \exp\left(-\frac{(y - (\mu + \sigma^2))^2}{2\sigma^2}\right) dy$$

$$= \exp\left(\mu + \frac{\sigma^2}{2}\right) P(N(\mu + \sigma^2, \sigma^2) > \ln k)$$

$$= \exp\left(\mu + \frac{\sigma^2}{2}\right) P(N(0,1) > \frac{\ln k - \mu - \sigma^2}{\sigma})$$

$$= \exp\left(\mu + \frac{\sigma^2}{2}\right) \left(1 - \phi\left(\frac{\ln k - \mu - \sigma^2}{\sigma}\right)\right)$$

$$= \exp\left(\mu + \frac{\sigma^2}{2}\right) \phi\left(\frac{\mu - \ln k + \sigma^2}{\sigma}\right)$$

Y VR lemnaral a ngl, videritiv men?

$$\left(\frac{\mu - \ln k - \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k - \sigma^2}{\sigma}} = \phi^{-\frac{\mu - \ln k - \sigma^2}{\sigma}}$$

$$\left(\frac{\mu - \ln k + \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k + \sigma^2}{\sigma}} =$$

$$\left(\frac{\mu - \ln k - \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k - \sigma^2}{\sigma}} - \left(\frac{\mu - \ln k + \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k + \sigma^2}{\sigma}} =$$

$$\left[\left(\frac{\mu - \ln k - \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k - \sigma^2}{\sigma}} - \left(\frac{\mu - \ln k + \sigma^2}{\sigma}\right) \phi^{-\frac{\mu - \ln k + \sigma^2}{\sigma}}\right] = \left((\mu - \ln k)^2\right) \phi^{-\frac{\mu - \ln k}{\sigma}}$$

(Q. 4)

(b)

put option: expiration date T on a forward maturing
at time $T' > T \Rightarrow$ payoff = $(K - F(T, T'))^+$

↳ Terminal payoff.

$$\text{Solve } F(T, T') = F(t, T') e^{(r-\delta-\frac{\sigma^2}{2})(T-t) + \sigma w_{T-t}^q}$$

Ex: Premium notes \rightarrow 3.5.1 (Page 30)

Eg (36):-

$$F(t, T') = S_t e^{(r-\delta)(T'-t)}$$

$$F(T, T') = S_T e^{(r-\delta)(T-t)}$$

$$\begin{aligned} \Rightarrow \frac{F(T, T')}{F(t, T')} &= \frac{S_T}{S_t} e^{(r-\delta)(t-T)} \\ &= e^{(r-\delta-\frac{\sigma^2}{2})(T-t) + \sigma(w_T^q - w_t^q)} e^{(r-\delta)(t-T)} \\ &= e^{-\frac{\sigma^2}{2}(T-t) + \sigma(w_T^q - w_t^q)} \end{aligned}$$

$$\Rightarrow F(T, T') = F(t, T') e^{-\frac{\sigma^2}{2}(T-t) + \sigma(w_T^q - w_t^q)}$$

$$\begin{aligned}
 (E) / P(t) &= e^{-r(T-t)} E^Q((K - F(t, T'))^+) \\
 &= e^{-r(T-t)} E^Q((K - F(t, T') e^{-\frac{\sigma^2}{2}(T-t) + \sigma(\omega_t^Q - \omega_{t'}^Q)})^+) \\
 &= e^{-r(T-t)} K E^Q((1 - \frac{F(t, T')}{K} e^{-\frac{\sigma^2}{2}(T-t) + \sigma(\omega_t^Q - \omega_{t'}^Q)})^+)
 \end{aligned}$$

Formula:

$$\begin{aligned}
 P &= K e^{-r(T-t)} N(-d_2) - S_t N(-d_1) \\
 &= K e^{-r(T-t)} N(-d_2) - F(t, T') e^{-r(T-t)} N(-d_1) \\
 &= e^{-r(T-t)} N(-d_2)
 \end{aligned}$$

$$so, P_0 = e^{-rt} (K N(-d_2) - F(0, T') N(-d_1))$$

where $d_1 = \ln(F(0, T')/K) + \frac{\sigma^2 T}{2}$, $d_2 = d_1 - \sigma\sqrt{T-t}$

$$= P_F = e^{-r(T-t)} (K N(-d_2) - F(t, T') N(-d_1))$$

where $d_1 = \ln(F(t, T')/K) + \frac{\sigma^2 (T-t)}{2}$, $d_2 = d_1 - \sigma\sqrt{T-t}$

$$(P \omega - P \omega)^2 + (t-T)^2 = (T, t)^2$$

(Q.4)

(c)

$$\text{price} = P_t = e^{-r(T-t)} E((K - F(t, T))^+)$$

$$= e^{-r(T-t)} K E\left(\left(1 - \frac{F(t, T)}{K}\right)^+\right)$$

lognormal ?

$$\ln\left(\frac{F(t, T)}{K}\right) = \ln\left(\frac{F(t, T)}{K} e^{r - \frac{\sigma^2}{2}(T-t) + \sigma(W_T^0 - W_t^0)}\right)$$

$$= \ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2}{2}(T-t) + \sigma(W_T^0 - W_t^0)$$

$$= N\left(\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2}{2}(T-t), \sigma^2(T-t)\right)$$

$$u_c = N\left(\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2 \Delta}{2}, \sigma^2 \Delta\right) \quad \text{where } \Delta = T-t$$

$$\Rightarrow P_t = e^{-r\Delta} K \left(\phi\left(-\frac{u_c}{\sigma_c}\right) - e^{u_c + \frac{\sigma^2}{2}} \phi\left(-\frac{u_c + \sigma_c}{\sigma_c}\right) \right)$$

$$= e^{-r\Delta} K \left[\phi\left(-\frac{\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2 \Delta}{2}}{\sigma \sqrt{\Delta}}\right) - e^{\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2 \Delta}{2} + \frac{\sigma^2 \Delta}{2}} \times \phi\left(-\frac{\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2 \Delta}{2} + \sigma \Delta}{\sigma \sqrt{\Delta}}\right) \right]$$

$$= e^{-r\Delta} K \left[\phi(-d_2) - \frac{F(t, T)}{K} \phi\left(-\frac{\ln\left(\frac{F(t, T)}{K}\right) - \frac{\sigma^2 \Delta}{2}}{\sigma \sqrt{\Delta}}\right) \right]$$

$$= e^{-r\Delta} K \phi(-d_2) - e^{-r\Delta} F(t, T) \phi(-d_1)$$

$$= e^{-r\Delta} \left(K N(-d_2) - F(t, T) N(-d_1) \right)$$

$$= \frac{e^{-r(T-t)} (K N(-d_2) - F(t, T) N(-d_1))}{e^{-r(T-t)} (K N(-d_2) - F(t, T) N(-d_1))}$$

$$\text{where } d_2 = \frac{\ln\left(\frac{F(t, T)}{K}\right) + \frac{\sigma^2(T-t)}{2}}{\sigma \sqrt{T-t}} \quad \text{and } d_1 = d_2 - \sigma \sqrt{T-t}$$

$$\begin{aligned}
 & \text{So, } \ln F(t, T') = \ln S_T e^{-\alpha(T'-t)} + m(1 - e^{-\alpha(T'-t)}) + \frac{\sigma^2}{4\alpha} (1 - e^{-2\alpha(T'-t)}) \\
 & \quad \left[\text{(Eqn 37 in notes)} \right] = Y_t e^{-\alpha(T'-t)} + m(1 - e^{-\alpha(T'-t)}) + \frac{\sigma^2}{4\alpha} (1 - e^{-2\alpha(T'-t)}) \\
 & \quad \left(Y_t \sim N \left(Y_0 e^{-\alpha t} + m(1 - e^{-\alpha t}), \frac{\sigma^2}{2\alpha} (1 - e^{-2\alpha(t)}) \right) \right) \\
 & \ln(F(t, T')) \sim N \left(Y_0 e^{-\alpha T'} + m(e^{-\alpha(T'-t)} - e^{-\alpha T'}) + m(1 - e^{-\alpha(T'-t)}) + \frac{\sigma^2}{4\alpha} (1 - e^{-2\alpha(T'-t)}) \right. \\
 & \quad \left. - \frac{\sigma^2}{2\alpha} (e^{-2\alpha(T'-t)} - e^{-2\alpha T'}) \right)
 \end{aligned}$$

$$\begin{aligned}
 & \text{So, } \ln F(t, T') = T_1(t, T) \ln S_T + T_2(t, T') + T_3(t, T') \\
 & \ln F(T, T') = T_1(T, T') \ln S_T \quad \text{where } T_1(a, b) = e^{-\alpha(b-a)} \\
 & \text{So, } \ln F(t, T') = T_1(t, T') \ln S_T + T_2(t, T') + T_3(t, T') \\
 & \ln F(t, T') = T_1(t, T') \ln S_T + T_2(t, T') + T_3(t, T')
 \end{aligned}$$

$$\begin{aligned}
 & \Rightarrow \ln F(T, T') - \ln F(t, T') = T_1(T, T') \ln S_T - T_1(t, T') \ln S_T \\
 & \quad + T_2(T, T') - T_2(t, T') + T_3(T, T') - T_3(t, T') \\
 & \quad \Downarrow T_4
 \end{aligned}$$

$$\begin{aligned}
 & = e^{-\alpha(T-T')} \ln S_T - e^{-\alpha(T-t)} \ln S_t + T_4 \\
 & = e^{-\alpha T'} (e^{\alpha T} \ln S_T - e^{\alpha t} \ln S_t) + T_4 \\
 & = e^{-\alpha T'} (e^{\alpha T} Y_T - e^{\alpha t} Y_t) + T_4 \quad \xrightarrow{\text{Eqn 37}} \\
 & = e^{-\alpha T'} (e^{\alpha T} (Y_t e^{-\alpha(T-t)} + m(1 - e^{-\alpha(T-t)})) + \sigma e^{-\alpha T} \int_t^T e^{\alpha u} dW_u^\alpha - e^{\alpha t} Y_t) + T_4 \\
 & = e^{-\alpha T'} (Y_t e^{\alpha T} + m(e^{\alpha T} - e^{\alpha t}) + \sigma \int_t^T e^{\alpha u} dW_u^\alpha - e^{\alpha t} Y_t) + T_4 \\
 & = m(e^{-\alpha(T'-T)} - e^{-\alpha(T'-t)}) + T_4 + \sigma \int_t^T e^{-\alpha(T-u)} dW_u^\alpha
 \end{aligned}$$

$T_4 = f^n(T_2, T_3)$ is deterministic, so $s \in M = \{T, s\} \cap n$. (b) (v-d)

$\ln F(T, T') - \ln F(t, T')$

$$\sim N(m(e^{-\alpha(T-t)} - e^{-\alpha(T'-t)}) + T_4, \sigma^2 \int_t^{T'} e^{-2\alpha(u-t)} du)$$

$$= N(m(e^{-\alpha(T-t)} - e^{-\alpha(T'-t)}) + T_4, \frac{\sigma^2}{2\alpha} (e^{-2\alpha(T-t)} - e^{-2\alpha(T'-t)}))$$

$\Rightarrow \ln F(T, T')$

$$\sim N(\ln F(t, T') + m(e^{-\alpha(T-t)} - e^{-\alpha(T'-t)}) + T_2(T, T') - T_2(t, T') + T_3(T, T') - T_3(t, T'))$$

$$\frac{\sigma^2}{2\alpha} (e^{-2\alpha(T-t)} - e^{-2\alpha(T'-t)})$$

$$S = (d, \alpha)_{\text{ET}}$$

$$(d, \alpha)_{\text{ET}} = (d, \alpha)_{\text{ET}}$$

$$(d, \alpha)_{\text{ET}} = (d, \alpha)_{\text{ET}}$$

$$(T, T)_{\text{ET}} + (T, T)_{\text{ET}} + \dots = (T, T)_{\text{ET}}$$

$$(T, t)_{\text{ET}} + (T, t)_{\text{ET}} + \dots = (T, t)_{\text{ET}}$$

$$2n((T, t)_{\text{ET}} - \text{rank}(T, T)_{\text{ET}}) = (T, t)_{\text{ET}} - (T, T)_{\text{ET}}$$

$$(T, t)_{\text{ET}} - (T, T)_{\text{ET}} + (T, t)_{\text{ET}} = (T, T)_{\text{ET}}$$

$$T \leftarrow$$

$$T + \text{rank}(T, T)_{\text{ET}} S = \text{rank}(T, T)_{\text{ET}} S =$$

$$T + (2n^2 - 1)_{\text{ET}} S =$$

$$T + (2n^2 - 1)_{\text{ET}} S =$$

$$T + (2n^2 - 1)_{\text{ET}} S = (2n^2 - 1)_{\text{ET}} S + (2n^2 - 1)_{\text{ET}} S =$$

$$T + (2n^2 - 1)_{\text{ET}} S = (2n^2 - 1)_{\text{ET}} S + (2n^2 - 1)_{\text{ET}} S =$$

$$T + (2n^2 - 1)_{\text{ET}} S = (2n^2 - 1)_{\text{ET}} S + (2n^2 - 1)_{\text{ET}} S =$$

(Q.4)

(e) Let $\ln F(T, T')$ $\sim N(\mu_e, \sigma_e^2)$ refer to part(d)

$$\Rightarrow P_t = e^{-r(T-t)} (K - F(T, T'))^+$$

$$= e^{-r(T-t)} K \left(1 - \frac{F(T, T')}{K} \right)^+$$

$$\text{Now, } \ln \left(\frac{F(T, T')}{K} \right) = \ln F(T, T') - \ln K$$

$$= N(\mu_e - \ln K, \sigma_e^2)$$

\Rightarrow Using part(a) of Φ ,

$$P_t = e^{-r(T-t)} K \left(\Phi \left(\frac{-(\mu_e - \ln K)}{\sigma_e} \right) - e^{\frac{(\mu_e - \ln K) + \sigma_e^2}{2}} \Phi \left(\frac{-(\mu_e - \ln K) - \sigma_e^2}{\sigma_e} \right) \right)$$

$$\Rightarrow P_t = e^{-r(T-t)} K \left(\Phi \left(\frac{-\mu_e - \ln K}{\sigma_e} \right) - e^{\frac{\mu_e - \ln K + \sigma_e^2}{2}} \Phi \left(\frac{-(\mu_e - \ln K) - \sigma_e^2}{\sigma_e} \right) \right)$$

$\overbrace{\hspace{10em}}$ $\overbrace{\hspace{10em}}$

$$\text{Here, } \mu_e = \ln \Phi F(t, T') + m(e^{-\alpha(T^L-T)} - e^{-\alpha(T^L-t)}) + T_2(T, T') - T_2(t, T')$$

$$+ T_3(T, T') - T_3(t, T')$$

$$+ \sigma_e^2 = \frac{\sigma^2}{2\alpha} (e^{-2\alpha(T^L-T)} - e^{-2\alpha(T^L-t)})$$

\downarrow
from part(d)

(Q.5) S_t = stock price

X_t = market Index

C(S) $\xrightarrow[\text{on index } X]{\text{bchmkd}} \text{pf} = (S_T - X_T)^+$ on date T.

Risk Neutral world : Q

(a) $w_t^{Q1} \perp \!\!\! \perp w_t^{Q2}$ are 2 BM.

Given: $B_t^Q = g w_t^{Q1} + \sqrt{1-g^2} w_t^{Q2}; g \in (-1, 1)$

To show: $B_t^Q = \text{BM}$.

Proof :- since $w_t^{Q1}, w_t^{Q2} = \text{BM}$,

$w_t^{Q1} \sim N(0, t), w_t^{Q2} \sim N(0, t)$ (Both w_t^{Q1} & w_t^{Q2} are scalars)

further since $w_t^{Q1} \perp \!\!\! \perp w_t^{Q2} \forall t$, ~~corr~~

$$\text{corr}(w_t^{Q1}, w_t^{Q2}) = 0$$

$$\Rightarrow \text{cov}(w_t^{Q1}, w_t^{Q2}) = 0$$

so, $B_t^Q = \text{linear combn of 2nd Gaussians}$

= Gaussian

$$E(B_t^Q) = g \cdot 0 + \sqrt{1-g^2} \cdot 0 = 0$$

$$\text{var}(B_t^Q) = g^2 \cdot t + (1-g^2)t + g\sqrt{1-g^2} \cdot 0 \\ = t$$

$$\Rightarrow B_t^Q \sim N(0, t)$$

Also, we need to prove some more things.

$$\begin{aligned} &\bullet N(0, 1) \\ &- \frac{1}{2} \left[\int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx \right]^2 \end{aligned}$$

Not separable in general,
but still Gaussian

(Q) How to prove that something is a Brownian Motion (BM)?

→ ① Stationary & ind^P increments : Since $W_t^{(1)}, W_t^{(2)}$ are BM, they have s.f.i. increments \Rightarrow so would B_t

② $B_0 = 0$: $B_0 = \beta W_0^{(1)} + \sqrt{1-\beta^2} W_0^{(2)} = \beta \cdot 0 + \sqrt{1-\beta^2} \cdot 0 = 0$

③ Continuity : Since $W_t^{(1)}$ & $W_t^{(2)}$ are continuous, so will be B_t

④ $B_t - B_s = \beta (W_t^{(1)} - W_s^{(1)}) + \sqrt{1-\beta^2} (W_t^{(2)} - W_s^{(2)})$
 $= \beta N(0, (t-s)) + \sqrt{1-\beta^2} N(0, t-s)$
 $= N(0, t-s)$: since β & $\sqrt{1-\beta^2}$ are constants

① $B_t \sim N(0, t)$

② $B_0 = 0$

③ Continuity

④ Stationary & ind^P increments

⑤ $B_t - B_s = N(0, t-s)$

$\Rightarrow Q.G.D.$

$$0 = 0 + \sqrt{t-s} \cdot V + 0 + \delta = (\frac{\delta}{\sqrt{t-s}})^2$$

$$0 + \sqrt{t-s} \cdot V + \frac{\delta}{\sqrt{t-s}} + \frac{\delta}{\sqrt{t-s}} = (\frac{\delta}{\sqrt{t-s}})^2$$

$$\textcircled{3} (t-s) \sim \frac{\delta^2}{V^2}$$

so since mean variance are constant

$$\begin{aligned}
 (b) E^Q(W_T^{Q_1} B_T^{Q_2}) &= E^Q(S W_T^{Q_1} + \sqrt{1-s^2} W_T^{Q_2}) \\
 &= E^Q(S(W_T^{Q_1})^2 + \sqrt{1-s^2} W_T^{Q_1} W_T^{Q_2}) \\
 &= s \cdot (T+o) + \sqrt{1-s^2} E(W_T^{Q_1}) E(W_T^{Q_2}) \\
 &= \underline{\underline{sT}}.
 \end{aligned}$$

(c) No arb price = $e^{-rT} E((S_T - X_T)^+)$ - $\textcircled{1}$

$$\begin{aligned}
 \text{Now, } \frac{dX_t}{X_t} &= rdt + \gamma dW_t^{Q_1} \\
 &\quad \downarrow (r - \frac{\gamma^2}{2})t + n W_t^{Q_1} \\
 \Rightarrow X_t &= X_0 e^{(r - \frac{\gamma^2}{2})t + n W_t^{Q_1}} \quad - \textcircled{2} \quad \textcircled{1} \\
 \text{Hence, } S_t &= S_0 e^{(r - \sigma^2/2)t + \sigma B_t^Q} \quad - \textcircled{2}
 \end{aligned}$$

so, putting $\textcircled{1}$ & $\textcircled{2}$ in $\textcircled{3}$,

$$\begin{aligned}
 \text{price (P)} &= e^{-rT} E((S_0 e^{(r - \sigma^2/2)T + \sigma B_T^Q} - X_0 e^{(r - \frac{\gamma^2}{2})T + n W_T^{Q_1}})^+) \\
 &= E((S_0 e^{-\sigma^2/2 T + \sigma B_T^Q} - X_0 e^{-n^2/2 T + n W_T^{Q_1}})^+)
 \end{aligned}$$

$$= E((S_0 \exp(-\frac{\sigma^2}{2}T + \sigma(s W_T^{Q_1} + \sqrt{1-s^2} W_T^{Q_2})))^+ - X_0 \exp(-\frac{\gamma^2}{2}T + n W_T^{Q_1}))$$

$$e^{-rT} E((S_T - X_T)^+)$$

$$(d) C = S_0 N(d_1) - K e^{-rT} N(d_2) \quad \text{where } d_1 = \frac{\ln(\frac{S_0}{K}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

we have:-

$$\hookrightarrow \cdot \text{ from } C = E(e^{-rT}(S_T - K)^+)$$

$$C = E(e^{-rT}(S_T - X_T)^+)$$

$$\Rightarrow C = S_0 N(d_1) - X_T e^{-rT} N(d_2)$$

$$\text{or. } C = e^{-rT} E(X_T (\frac{S_T - X_T}{X_T})^+)$$

using change of numeraire,

$$\text{let } \frac{d\phi'}{d\phi} = X_T = X_0 e^{(r - \frac{\sigma^2}{2})T + n w_T^{\phi'}}$$

$$\begin{aligned} S_0 & \frac{S_T}{X_T} = \frac{S_0}{X_0} e^{(r - \frac{\sigma^2}{2})T + \sigma B_T - (r - \frac{\sigma^2}{2})T - n w_T^{\phi'}} \\ & = \frac{S_0}{X_0} e^{\frac{\sigma^2 - \sigma^2}{2}T + \sigma B_T - n w_T^{\phi'}} \end{aligned}$$

Now, using Margrabe's formula, \rightarrow Intermittent

$$Pf = \frac{(S_T^1 - S_T^2)^+}{q_1 - q_2} \rightarrow C = e^{-q_1 T} S_0^1 N(d_1) - e^{-q_2 T} S_0^2 N(d_2)$$

$$\text{where } d_1 = \ln\left(\frac{S_0^1}{S_0^2}\right) + (q_2 - q_1 + \frac{\sigma^2}{2})T$$

In our case,

$$S_T^1 = S_T, \quad S_T^2 = X_T$$

$$\begin{aligned} \text{yield} & \downarrow \\ \text{vol} & \downarrow \\ \text{corr} & \downarrow \end{aligned} \quad \begin{aligned} r &= r \\ \sigma &= \sigma \\ n &= n \end{aligned}$$

$$\text{where } \sigma = \sqrt{\sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \rho}$$

$$C = e^{-rT} (S_0 N(d_1) - X_0 N(d_2))$$

$$\text{where } d_1 = \ln\left(\frac{S_0}{X_0}\right) + \frac{\tilde{\sigma}^2 T}{2}; \quad \tilde{\sigma} = \sqrt{\sigma^2 + n^2 - 2n\rho}$$

$$d_2 = d_1 - \tilde{\sigma}\sqrt{T}$$

$$\begin{aligned} \tilde{\sigma} &= \sigma \\ K &= X_0 \\ T &= n \end{aligned}$$

Sq. If $E^Q(X_T H) = E^{Q^X}(H)$,
then $\frac{dQ^X}{dQ} = e^{-rT} \frac{x_T}{x_0} = e^{-r(T-t)} \frac{x_T}{x_t}$

Assumption: ~~Under Q, $e^{-rt} X_t$ is a martingale~~

$$S_t = S_0 e^{(r - \frac{\sigma^2}{2})t + \sigma B_t}$$

$$E(S_t) = S_0 e^{rt} = E(e^{-rt} S_t) = S_0$$

* Who all are mtgl?

$$\rightarrow f_t$$

$$\rightarrow \mathbb{E}^Q e^{-rt} S_t$$



Then: - If X_t is a martingale under Q ,

$$\text{then } E^Q(X_T H) = \mathbb{E}^{Q^X}(X_0 H)$$

$$\text{where } \frac{dQ^X}{dQ} = \frac{x_T}{x_0}.$$

$$\text{So, } E^Q(X_T H) = \int x_t H dQ = \int x_t H \frac{dQ^X}{dQ} dQ$$

$$= \int x_0 H dQ^X$$

$$= E^{Q^X}(X_0 H)$$

$$= X_0 E^{Q^X}(H)$$

In our case, $e^{-rT} X_T$ is a martingale under \mathbb{Q} .

$$\begin{aligned}
 \text{So, } & \text{ price of benchmarked call} \\
 & e^{-rT} \mathbb{E}^{\mathbb{Q}}((S_T - X_T)^+) = e^{-rT} \mathbb{E}^{\mathbb{Q}}(X_T (\frac{S_T}{X_T} - 1)^+) \\
 & = \mathbb{E}^{\mathbb{Q}}((e^{-rT} X_T) (\frac{S_T}{X_T} - 1)^+) \\
 & = \mathbb{E}^{\mathbb{Q}}((e^{-r_{\mathbb{Q}} t} X_0) (\frac{S_T}{X_T} - 1)^+) \\
 & = \mathbb{E}^{\mathbb{Q}}(X_0 (\frac{S_T}{X_T} - 1)^+) \\
 & = \boxed{X_0 \mathbb{E}^{\mathbb{Q}}((\frac{S_T}{X_T} - 1)^+)} - \textcircled{4}.
 \end{aligned}$$

Now, when $P_t = (S_t - K)^+$, $\frac{dS_t}{S_t} = rdt + \sigma dW_t$

Hence $\ln(\frac{S_t}{X_t}) = \ln(\frac{S_0}{X_0})$

$$S_t = f(S_t, X_t)$$

$$\begin{aligned}
 d(\frac{S_t}{X_t}) &= \cancel{\frac{1}{X_t} dS_t} - \frac{\partial f}{\partial S_t} dS_t + \frac{\partial f}{\partial X_t} dX_t + \frac{1}{2} \left(\frac{\partial^2 f}{\partial S_t^2} (dS_t)^2 + \cancel{\frac{\partial^2 f}{\partial X_t^2} (dX_t)^2} \right. \\
 &\quad \left. + 2 \frac{\partial^2 f}{\partial S_t \partial X_t} dS_t dX_t \right)
 \end{aligned}$$

$$\begin{aligned}
 \Rightarrow d(\frac{S_t}{X_t}) &= \cancel{\frac{1}{X_t} dS_t} - \frac{S_t}{X_t^2} dX_t + \frac{1}{2} \left(0 \cdot (dS_t)^2 + 2 \frac{S_t}{X_t^3} (dX_t)^2 + \cancel{\frac{1}{X_t^2} dS_t dX_t} \right) \\
 &= \frac{S_t}{X_t} (rdt + \sigma dB_t^{\mathbb{Q}}) - \frac{S_t}{X_t} (rdt + \eta dW_t^{\mathbb{Q}}) + \frac{1}{2} \left(\frac{2S_t}{X_t} \left(\frac{dX_t}{X_t} \right)^2 - 2 \frac{S_t}{X_t} \left(\frac{dS_t}{X_t} \right) \left(\frac{dX_t}{X_t} \right) \right) \\
 &= \frac{S_t}{X_t} (rdt + \sigma dB_t^{\mathbb{Q}} - rdt - \eta dW_t^{\mathbb{Q}} + \eta^2 dt - \sigma \eta s dt)
 \end{aligned}$$

$$\Rightarrow \mathbb{H} \frac{S_t}{X_t} = Z_t,$$

$$\begin{aligned}
 \frac{dZ_t}{Z_t} &= (\eta^2 - \sigma \eta s) dt + \sigma dB_t^{\mathbb{Q}} - \eta dW_t^{\mathbb{Q}} \\
 &= (\eta^2 - \sigma \eta s) dt + (\xi s - n) W_t^{\mathbb{Q}} + \sigma \sqrt{1-s^2} W_t^{\mathbb{Q}}
 \end{aligned}$$

$$\Rightarrow \frac{dZ_t}{Z_t} = \eta(n-\sigma s)dt + \sqrt{\sigma^2 s^2 + \eta^2 - 2\sigma \eta s + \sigma^2 - \tilde{\sigma}^2 s^2} dW_t^{\text{new}}$$

$$= \boxed{\eta(n-\sigma s)dt} + \boxed{\sqrt{\sigma^2 + \eta^2 - 2\sigma \eta s} dW_t^{\text{new}}}$$

$$= \tilde{r} dt + \tilde{\sigma} dW_t^{\text{new}} \rightarrow \text{This leads to:}$$

$$Z_T = Z_0 \exp\left(\tilde{r} - \frac{\tilde{\sigma}^2}{2} T + \tilde{\sigma} W_T^{\text{new}}\right)$$

$$= Z_0 \exp\left(\left(n^2 - \sigma^2 s^2 - \frac{1}{2}(\sigma^2 + n^2 - 2\sigma \eta s)\right)T + \tilde{\sigma} W_T^{\text{new}}\right)$$

$$= Z_0 \exp\left(\frac{(n^2 - \sigma^2)}{2} T + \tilde{\sigma} W_T^{\text{new}}\right)$$

So, we have:-

$$C = x_0 E^{\tilde{\sigma}}((Z_T - 1)^+)$$

$$= x_0 \left(Z_0 N(\tilde{d}_1) - 1 \cdot e^{-\tilde{r}T} N(\tilde{d}_2) \right)$$

where $\tilde{d}_1 = \frac{\ln(Z_0) + (\tilde{r} + \frac{\tilde{\sigma}^2}{2})T}{\tilde{\sigma}\sqrt{T}}$, $\tilde{d}_2 = \tilde{d}_1 - \tilde{\sigma}\sqrt{T}$

$$= x_0 \left(\frac{S_0}{x_0} N(\tilde{d}_1) - e^{-\tilde{r}T} N(\tilde{d}_2) \right)$$

where $\tilde{d}_1 = \frac{\ln(\frac{S_0}{x_0}) + (\tilde{r} + \frac{\tilde{\sigma}^2}{2})T}{\tilde{\sigma}\sqrt{T}}$, $\tilde{d}_2 = \tilde{d}_1 - \tilde{\sigma}\sqrt{T}$

$$= \boxed{\frac{S_0 N(\tilde{d}_1)}{x_0} - x_0 e^{-\tilde{r}T} N(\tilde{d}_2)}$$

$$= \boxed{C_{BS}(S_0, x_0, T, \tilde{r}, \tilde{\sigma})}$$

$$= C_{BS}(\tilde{S}_0, \tilde{x}_0, T, \tilde{r}, \tilde{\sigma})$$

where $\tilde{S}_0 = S_0$

$$\tilde{x}_0 = x_0$$

$$\tilde{r} = n(n-\sigma s)$$

$$\tilde{\sigma} = \sqrt{\sigma^2 + \eta^2 - 2\sigma \eta s}$$